

Leveraging Business Intelligence to Elevate Customer Experience in Small and Medium-Sized Enterprises

Munib Ahmad Alsoud

Jerash University

Corresponding Author Email: M.Alsoud@jpu.edu.jo

DOI Link: <http://dx.doi.org/10.6007/IJARBS/v16-i9/28920>

Published Date: 09 September 2026

Abstract

Small and medium-sized enterprises (SMEs) face significant challenges that compel them to continuously enhance their customer service quality to remain competitive in dynamic markets. This study examines the role of Business Intelligence (BI) in transforming vast amounts of customer interactions into actionable strategies, thereby improving service quality. Furthermore, it explores the capabilities of business intelligence in enabling SMEs to anticipate customer needs rather than merely reacting to them, fostering greater customer satisfaction and loyalty. To empirically validate these relationships, data were analyzed using SmartPLS (Partial Least Squares Structural Equation Modeling). The empirical findings reveal a substantial and significant impact business intelligence on service quality enhancement, with the structural model demonstrating a strong explanatory power where $R^2 = 0.731$, indicating that 73.1% of the variance in customer service quality is explained by the investigated BI capabilities. Strategic applications—such as real-time responsiveness and proactive adjustments—are also highlighted as critical drivers for operational excellence in SMEs.

Keywords: Business Intelligence, Customer Service Quality, Small and Medium-Sized Enterprises

Introduction

Small and medium-sized enterprises (SMEs) currently face significant challenges—particularly regarding the quality of service provided to customers—compelling them to adopt strategies that enhance operational efficiency and drive success amidst fierce external competition. Given the vital role SMEs play in the Jordanian economy and their contribution to sustainable development, this article examines the theoretical and practical aspects of how business intelligence creates opportunities for these enterprises to improve service quality, thereby enabling them to achieve their goals and aspirations.

Business intelligence has become critically important for small and medium-sized enterprises (SMEs), particularly in the current landscape, emerging as a key area of interest for both business owners and researchers alike. This significance stems from the concept's ability to drive development, growth, excellence, and sustainability over both the short and long term. Consequently, this article aims to examine the positive impact of business intelligence on the quality of services provided by these companies.

This article introduces a connection not previously explored in other studies, aiming to elucidate new concepts and dimensions that have not been examined before; it thus seeks to bridge this gap and enable small and medium-sized enterprises (SMEs) to leverage the findings regarding business intelligence—and its dimensions—to enhance customer service quality.

With the advent of the third millennium—and particularly in light of the knowledge economy, technological advancements, and rapid changes in the internal and external environments of organizations—small and medium-sized enterprises (SMEs) are compelled to harness the strengths and progress stemming from the knowledge economy and technology-driven systems. Consequently, knowledge serves as a fundamental source of business intelligence within organizations, and the attainment of competitive advantage relies on the quality of decisions made (Yassin, 2018,38). Decision-makers thus have a critical need for data, information, and knowledge to comprehend the business environment. Such data may originate internally—from personnel and processes—or externally, from competitors and the surrounding business landscape; therefore, the data must be structured and organized to ensure it can be effectively utilized by users (Bajgoric, 2010, 20).

On the other hand, the quality of services is currently of great importance to both service providers and beneficiaries. This significance has raised awareness among small and medium-sized enterprises (SMEs) regarding the need to improve service quality to secure beneficiary satisfaction and loyalty—a process that requires the effective use of business intelligence and information and communication technology (Al-Taweel, 2020). Service quality is a key concept for researchers and decision-makers alike, having been the subject of extensive research. Some studies have focused on defining the concept; notably, service quality was first defined in 1983 as a measure of the extent to which the service level aligns with the recipient's expectations. The environment in which services are delivered is a crucial aspect for the customer and significantly influences their perception of the organization; therefore, it is essential to involve customers in defining this environment and to consider their views and expectations when shaping it (Qattaf & Bazqarari, 2019, 72). In this article, we will explain the concept of service quality, as well as the methods used to measure and improve it.

Despite the extensive research addressing business intelligence and service quality, there remain differences of opinion among researchers regarding the dimensions encompassed by each. Consequently, this article focuses on—and links—dimensions that, to the best of the researcher's knowledge, have not previously been combined in earlier studies.

Literature Review

Ahmadi et al. (2021) conducted research to examine the role of business intelligence—across all its dimensions (information content quality, analytical processing, reporting quality, and

content access quality)—in achieving financial reporting quality. The results demonstrated that business intelligence components have a positive impact on financial reporting quality; furthermore, the study highlighted that a decision-making culture grounded in business intelligence plays a positive and direct role in the quality of financial reports. A study was also conducted in Indonesia by Rosita and Wulandari (2021) regarding the role of business intelligence—across its various dimensions (data sources, data warehouses, data mining, and report presentation)—in the automation of medical records. The results demonstrated that utilizing business intelligence for medical record automation facilitates communication between service providers and recipients, safeguards the legal interests of both patients and hospitals, and enhances the speed and accuracy of medical record management systems.

Another study by Sechi et al. (2020) in Italy highlighted the role of business intelligence—encompassing analytical processing, data warehousing, emergency service quality, and response speed—in addressing the SARS-CoV-2 epidemic. The findings demonstrated that business intelligence is valuable for identifying epidemic clusters and patterns; it facilitates timely decision-making, improves emergency management responses, and enables resource reallocation based on data generated through business intelligence systems.

Additionally, a study by Mbima and Tettehi (2023) in Ghana investigated the role of business intelligence in operational performance among small and medium-sized enterprises (SMEs), with supply chain ambidexterity serving as a mediating variable. The results demonstrated that business intelligence has a significant positive impact on operational performance in SMEs, mediated by supply chain ambidexterity.

Another study by Aun (2021) on Portland Paints and Products in Nigeria focused on the impact of business intelligence—specifically its dimensions of organizational learning, information gathering, and information storage—on corporate performance. The results demonstrated that business intelligence, across these dimensions, has a clear impact on corporate performance; furthermore, the study revealed that organizational learning influences both employee commitment and information gathering.

Al-Nsour's study examined the role of business intelligence in the quality of customer services provided by banks. The researchers employed a data analysis methodology using business intelligence systems to understand customer behavior and expectations. The results demonstrated that implementing business intelligence significantly reduces response times to customer requests, facilitates more effective complaint resolution, and enhances customer satisfaction and loyalty (Al-Nsour et al., 2024). Meanwhile, Lin's study investigated the impact of business intelligence systems and data analysis on Customer Relationship Management (CRM) within the e-retail sector. The findings revealed that smart dashboards and data mining enhance companies' ability to predict customer needs and provide personalized recommendations, thereby improving service quality and increasing customer retention rates (Lin et al., 2023).

Obeidat investigated the impact of business intelligence capabilities on supporting marketing performance in small and medium-sized service enterprises. The findings highlighted that the analytical capabilities of business intelligence enhance decision-making quality and assist

management in rapidly identifying weaknesses in audience communication, thereby positively influencing service quality for customers (Obeidat et al., 2023).

Similarly, an article by Akter focused on measuring the impact of information quality derived from business intelligence systems on the empowerment of customer service personnel in the telecommunications sector. The results demonstrated that providing accurate, up-to-date documentation through business intelligence systems boosts employees' ability to resolve customer issues during the initial contact (First Contact Resolution), which contributes to increased operational efficiency and maximizes the value delivered to the customer (Akter et al., 2021).

Finally, the study by Manikam et al. (2019) examined business intelligence—encompassing real-time analytical processing, data warehousing, and data mining—in the context of service quality. The findings highlighted that internal collaboration is essential for achieving service quality and indicated that public institutions are evaluating how to manage the variety, volume, and velocity of underutilized service assets, necessitating timely analysis.

Significance of the Article and the Research Gap

This article offers significant value and makes multiple contributions. First, it is one of the few studies to examine the impact of business intelligence system dimensions on improving the quality of customer service. Second, it is distinguished by the specific variables it investigates, as there is a scarcity of research examining these variables and their dimensions collectively. Third, the study links new dimensions of the business intelligence concept with those of customer service, addressing the lack of existing research connecting the two.

To the best of the researcher's knowledge, and based on prior studies examining the variables of this research (business intelligence and customer service quality), most such studies have been conducted in diverse environments. Accordingly, this study is situated in a relevant context by focusing on the small and medium-sized enterprise (SME) sector, which is experiencing significant growth alongside rapid and continuous development.

On the other hand, while prior scholarly work e.g. [Akter et al., 2021; Johnson & Smith, 2024] have extensively examined the isolated impacts of business intelligence tools on organizational metrics, a critical gap persists regarding how an integrated framework of business intelligence dimension specifically (data warehousing, data mining, OLAP, and information visualization) collectively drives service quality enhancements. Most existing literature tends to report individual technological impacts rather than synthesizing how these components interact synergistically, particularly within the context of (SMEs) in Jordan. Jordanian SMEs operate under unique market dynamics and resource constraints that require agile, data-driven decision-making. Therefore, this article addresses this critical void by empirically evaluating the comprehensive integration of these four Business intelligence dimensions, providing distinct theoretical and practical contributions to the strategic performance and customer service quality of Jordanian SMEs.

Business Intelligence and Customer Service Quality

The concept of Business Intelligence (BI) centers on utilizing systems, technology, and data analysis methods to transform raw data into meaningful insights that can enhance corporate

performance. It serves as a key organizational component that enables companies to maximize profitability. In today's landscape, a failure to employ BI hinders the ability to identify profit potential; thus, it stands as a powerful tool for organizations to improve their operations and overall performance. By leveraging data and analytics, companies can optimize processes, seize opportunities, enhance service quality, and gain a competitive advantage (Junaedi et al., 2023). Business Intelligence (BI) systems are a cornerstone of modern organizations, transforming data into reliable, accurate information that facilitates timely strategic and mid-level decision-making (Rayyal et al., 2022). Furthermore, BI is vital for enabling leaders to anticipate future trends and analyze consumer behavior; this helps reduce operational costs and enhance performance efficiency by eliminating haphazard approaches and relying instead on precise digital evidence (Chapod et al., 2023).

Given that the current dynamic and ever-changing environment demands rapid and effective decision-making, business intelligence facilitates the collection of vast amounts of data that cannot be extracted manually. This empowers organizations to adapt their services to market fluctuations and customer needs, as well as to capitalize on opportunities by leveraging critical insights—such as market trends, customer opinions and preferences, and competitor activities—to make informed decisions and enhance their strategies, quality, and performance (Kazemi et al., 2023).

On the other hand, business intelligence supports decision-making at all organizational levels by analyzing, integrating, and disseminating critical business information through a range of specialized techniques and tools (Kale, 2015, 366). Furthermore, the importance of business intelligence lies in its ability to facilitate an understanding of a business environment characterized by fierce competition and frequent shifts; it enables real-time monitoring and forecasts future trends, aiming to achieve comprehensive quality across all business operations (Alshehadeh et al., 2023).

The primary objectives of business intelligence are to improve the quality of decision-making processes, increase profitability, and enhance customer satisfaction by gaining a deep understanding of customer needs and preferences (Lawson, 2021). These systems also aim to unify organizational data sources by establishing centralized data repositories that enable various administrative departments to access standardized, real-time reports; this fosters transparency and accelerates responsiveness to rapid changes within the competitive business environment (Johnson & Smith, 2024).

To achieve these objectives, the business intelligence architecture comprises several integrated layers, starting with diverse data sources (such as databases and ERP systems), progressing through data warehouses and data cubes that organize information, and culminating in end-user presentation tools—such as dashboards and advanced analytical reports—utilized by decision-makers (Watson, 2023). This structural integration ensures the seamless and accurate flow of data from the point of collection to its transformation into immediately actionable insights.

Based on the foregoing, the importance of business intelligence lies in its role as a vital tool for small and medium-sized enterprises (SMEs). It transforms data into actionable strategic insights, thereby enhancing their ability to respond to rapid changes and evolving customer

needs. Furthermore, it facilitates sound decision-making—enabling businesses to boost competitiveness, efficiency, and customer satisfaction through opportunity identification and market analysis—ultimately leading to sustainable success.

On the other hand, Continuous quality improvement is a primary goal and objective for all companies, as it enables them to secure a strong market position, realize their vision, and ensure long-term sustainability. Ibrahim (2022) defines the service quality improvement process as the implementation of adjustments designed to enhance service quality and ensure corporate continuity in both the short and long term, while also identifying the specific characteristics and requirements for such improvements. Adopting Total Quality Management (TQM) practices is currently considered one of the most significant modern approaches for organizations; it guarantees improved service quality and fosters customer satisfaction and loyalty. This process relies on direct support from senior management—manifested through implementation, employee empowerment, a customer-centric focus, and a commitment to continuous improvement—to drive development and progress (Al-Hakami et al., 2022).

Improving the quality of services or products is a key strategy organizations employ to maintain their market continuity; service quality improvement is defined as a method of gaining customer loyalty by meeting their desires and expectations and delivering services that approach perfection (Besterfield et al., 2018). The researcher maintains that achieving such improvement is impossible without implementing business intelligence dimensions, given the critical data they provide to small and medium-sized enterprises (SMEs)—data that facilitates decision-making, selection, and improvement processes, particularly amidst the constantly shifting nature of customer expectations and desires.

The literature identifies two strategies for continuous improvement: Juran's strategy and the Kaizen strategy. Juran's strategy—named after Joseph Juran, a preeminent figure in the field of quality—emphasizes the need for a significant shift in corporate culture to foster an environment conducive to innovation and creativity. It posits that problem-solving requires a systematic, scientific approach: gathering information about the problem, identifying and narrowing down its primary causes, proposing optimal solutions, and evaluating them to select the best course of action. Juran also focuses on addressing defects, inefficiencies, and wasted time within daily operations, while underscoring the importance of senior management commitment, the implementation of training workshops, and the continuous improvement of processes. On the other hand, the primary objective of the Kaizen strategy is to demonstrate how companies can achieve their goals by minimizing waste in terms of resources, time, and effort. The term "Kaizen" signifies "change for the better," as the strategy is grounded in the principle of incremental improvement; this approach contributes to cost reduction, increased productivity, and the enhancement of workers' innovative capabilities (Shaaban, 2009, 34; Abu Al-Nasr, 2015, 64–65).

Tahar and Maayouf (2019) indicated that business intelligence and e-management play a significant role in improving service quality. Furthermore, enhancing the overall nature of the service offers various advantages across different levels: at the marketing level, specific attributes are established to differentiate the service from others; commercially, the promises

made by companies in their advertising campaigns are fulfilled; and administratively, efforts are directed toward ensuring alignment with all internal specifications.

Dimensions of Business Intelligence

Researchers' perspectives on the dimensions of business intelligence vary; this article will adopt the following key dimensions:

Data Warehouse

The term "data warehouse" emerged in the 1980s to facilitate the continuous collection, organization, and summarization of data regarding organizational operations, thereby enabling the effective storage, management, and retrieval of vast amounts of data (Awad & Mahmoud, 2024, 44; Nataraja & Galety, 2024, 4). Sharda et al. (2022, 63) defined a data warehouse as a large collection of data—derived from current and historical records as well as various corporate sources—that is transformed and loaded into a repository to support decision-making processes. Furthermore, Sherman (2015, 91) explained that a data warehouse stores an organization's current and historical data—collected from multiple systems—utilizing information technology to identify, manage, and control that data.

Data Mining

Data mining is defined as a process involving the systematic exploration and analysis of massive datasets—using various statistical and computational methods—to uncover patterns and correlations (Natarajan & Galety, 2024, 4). Sherman (2015, 17) also defined data mining as the process of analyzing vast quantities of data to identify various patterns—such as record clusters, anomalies, and dependencies—thereby enabling organizations to discover previously unknown or undefined patterns and relationships.

It can also be defined as the process of extracting previously unknown, implicit information from data—information that can be useful for identifying relationships and patterns within massive databases. Data mining comprises a set of techniques that help identify decision-relevant information or knowledge within datasets and extract it in a manner that facilitates its use in areas such as decision support, forecasting, and estimation (Binzafrah & Taleedi, 2022). Data mining reveals essential relationships and patterns within vast amounts of data, transforming them into information that can be leveraged to support decision-making and enhance performance levels.

Real-time analytical processing offers numerous methods for gathering data from various sources and analyzing it to extract insights that benefit the organization; it also enables data exploration from multiple perspectives (Lamani et al., 2019). Natarajan and Balety (2024, 4) emphasized that it is a technique facilitating the study of data across multiple dimensions, allowing users to perform complex calculations and examine data from various viewpoints.

Online Analytical Processing (OLAP)

Online Analytical Processing (OLAP) is defined as a technology that supports analysis and decision-making; it facilitates the analysis of vast amounts of data across multiple dimensions, focusing on the interactive exploration of multidimensional data at various levels of granularity (Sabherwal & Fernandez, 2011, 41).

It is also defined as a subset of business intelligence—encompassing relational databases, data mining, and report generation—that handles complex multidimensional queries (Alomari & Çengel, 2023). Furthermore, Bussa (2023) noted that OLAP simplifies multidimensional data analysis and enables operations such as drill-down, slicing, aggregation, and partitioning.

Information visualization

Information visualization is defined as the method of utilizing tools and techniques to display information following the analysis process; it is considered a fundamental process in business intelligence, as it enables decision-makers to more easily comprehend complex datasets (Bussa, 2023).

Business intelligence focuses on data preparation and integration, as well as delivering analytics to users through a variety of formats—including text, reports, visualizations, dashboards, graphics, summaries, charts, and maps (Gupta et al., 2021).

The success of business intelligence also depends on the effectiveness of information presentation; the efficient communication of system outputs—achieved through various technologies—represents the visible component of business intelligence systems. Consequently, the efficiency of these technologies is measured by their ability to present information in a manner that directly connects with the user, facilitating comprehension and enabling informed decision-making (Binzafrah & Taleedi, 2022).

Dimensions of Customer Service Quality

Researchers' perspectives on the dimensions of business intelligence vary; this article will adopt the following key dimensions:

Responsiveness

Responsiveness is defined as an organization's ability and willingness to meet customer needs and expectations through efficient, rapid, and effective service delivery; it serves as a measure of service quality and the speed with which customer expectations are met.

Parasuraman et al. (1988) view responsiveness as the staff's commitment to assisting customers and providing services promptly and in a timely manner. In the context of e-services, Parasuraman et al. (2005) noted that responsiveness becomes evident when a customer encounters a problem or requires assistance; it is linked to the speed of support provision and the ability to efficiently address customer expectations and issues. Consequently, a company's ability to enhance its responsiveness strengthens customer perceptions of, and loyalty to, both the service and the service provider.

Reliability

Reliability is defined as the process of delivering a service correctly, based on the accuracy, integrity, and currency of the information involved. Parasuraman et al. (2005) demonstrated that service reliability is linked to an organization's ability to deliver services that precisely meet customer expectations, ensuring the execution of requests and the provision of services and information without errors. Thus, reliability refers to a system's ability to remain stable and fulfill its obligations to the customer.

Tangibles

Tangibles refer to the physical arrangements associated with service delivery and the organization of physical elements—such as equipment and facilities—within the organization. Van Iwaarden et al. (2003) emphasized that tangibles are not limited to equipment and facilities in traditional service environments but also apply to websites. In an online environment, tangibles encompass the website's appearance, search options, ease of navigation, and the organization and design of its structure. Consequently, a well-organized service design is a key factor in helping customers form a positive impression of service quality.

Assurance/Security

This is defined as the organization's ability to build a bond of trust and security with customers, thereby ensuring the safety of their experience and the quality of the service. Van Iwaarden et al. (2003) noted that assurance in service delivery relates to the organization's ability to convey a sense of confidence and trust to the customer, particularly regarding privacy and security. This dimension is highly significant to customers because it safeguards their personal and financial information; consequently, the customer's perception that their transactions and data are protected helps strengthen their trust in the service provider.

Study Problem

This research aims to examine the issues faced by small and medium-sized enterprises (SMEs) in an increasingly competitive, ever-changing business environment where customers today expect a greater level of service standards, product quality and responsiveness than ever before. Although technology is becoming more prevalent, the majority of these companies do not yet make effective use of big data and the conversion of big data into strategic insights. Thus negatively affecting their customer understanding and ability to rightly meet their ever-evolving needs.

Many studies have been published regarding business intelligence (BI) technologies as well as the relative importance of customer experiences. However, there still exists a clear gap in research regarding the practical mechanisms through which BI tools can translate into a qualitative jump in customer experience. This is especially for the small and medium-sized enterprise (SME) sector that faces constraints regarding the technical and human resource frontiers.

Thus, the problem of the study is defined as answering the following main question: What is the impact of investing in business intelligence – across its various dimensions – on the enhancement of customer experience of MSMEs?

Hypotheses

Business intelligence with its dimensions of data warehousing, data mining, Online Analytical Processing (OLAP), and information visualization—does not improve the quality of customer service with its dimensions of responsiveness, reliability, tangibles, and assurance/security.

Study Methodology

This article employed a sampling approach targeting a group of small and medium-sized enterprises (SMEs) operating in the Governorate of Amman, Jordan, with the study covering

40 companies. A 32-question questionnaire was distributed to these companies between May and July 2026; three questionnaires were administered per company, resulting in a total of 120 distributed questionnaires.

In creating the survey tool, researchers used indicators of items from variables previously conducted using researchers' studies and adapted them to the study context. The parameters were measured through a questionnaire made on a Likert scale from 1 to 5 (1 = Agree very low degree, 2 = Agree low degree, 3 = Agree medium degree, 4 = Agree high degree, 5 = Agree very high degree.).

The study data were analyzed using Structural Equation Modeling (SEM) via SmartPLS; the analysis proceeded by first examining the outer model, then the inner model, and finally testing the main research hypothesis. The study population consisted of senior and middle-level managers from 40 small and medium-sized enterprises (SMEs).

The article utilized a questionnaire for data collection, distributing it to a random sample representative of the study population. This sample consisted of 120 managers from middle and senior management; three questionnaires were distributed to each company, resulting in a total of 120 questionnaires across 40 companies. The data were then analyzed using the following statistical measures:

First, Cronbach's alpha: to assess the internal consistency of the study's scales.

Second, Pearson correlation: to examine the inter-correlations among the dimensions of the independent variable.

Third, Skewness and kurtosis tests: to examine the distribution of the study's data.

Finally, Structural Equation Modeling (SEM) using SmartPLS software: to examine the direct and indirect effects of the study's variables.

Data Analysis

Table 1

personal variables

Variable	Items	Count
Gender:	Male	63
	Female	57
Age :	Less than 30 years	40
	30 Under 40 years old	36
	40 years and above	44
Number of experience	Less than 5 years	33
	5 years – less than 15 years	56
	15 years and above	31

Table (1) illustrates the distribution of the study sample, comprising 120 participants. Regarding gender, males constituted the majority with 63 individuals, while there were 57 female participants. In terms of age, the table shows a relatively even distribution across age groups: 40 participants were under the age of 30, 36 participants fell into the 30–39 age bracket, and 44 participants were aged 40 or older.

Finally, regarding years of experience, the table reveals that the majority of the sample possesses a moderate level of experience: 56 individuals have between 5 and less than 15 years of experience, 33 participants have less than 5 years, and 31 individuals have 15 years or more. These indicators and figures demonstrate the diversity and balanced distribution of the sample, thereby supporting the results and reliability of the statistical analysis.

Description of the dimensions of the study variables

Table 2

The standard deviation, arithmetic mean, rank, and relative importance of individuals answers to the Business intelligence variable and its dimensions

	Dimensions:	Mean:	Standard deviation:	Rank:	Results
1	<i>data warehousing</i>	4.312	0.717	2	<i>High</i>
2	<i>data mining</i>	4.212	0.703	4	High
3	<i>Oline Analytical Processing (OLAP)</i>	4.288	0.720	3	High
4	<i>information visualization</i>	4.320	0.721	1	High
<i>General rate</i>		<i>4.283</i>			<i>High</i>

Source: results of the Smart PLS

The analysis results presented in Table 2 indicate a high level of relative importance for business intelligence within small and medium-sized enterprises (SMEs); the overall mean score for business intelligence was 4.283, with the means of its individual dimensions ranging from 4.212 to 4.320. The "information visualization" dimension ranked first (mean: 4.320; standard deviation: 0.721), while the "data mining" dimension ranked last (mean: 4.212; standard deviation: 0.703). These findings highlight the significant relative importance of all business intelligence dimensions and demonstrate the commitment of SMEs to adopting these dimensions within their operations to address evolving customer trends and changing needs.

Table 3

The standard deviation, arithmetic mean, rank, and relative importance of individuals answers to the quality of customer service and its dimensions

	Dimensions	Mean	Standard deviation	Rank	Results
1	<i>responsiveness</i>	4.519	0.712	2	<i>High</i>
2	<i>reliability</i>	4.321	0.854	4	High
3	<i>tangibles</i>	4.355	0.800	3	High
4	<i>assurance/security</i>	4.542	0.898	1	High
<i>General rate</i>		<i>4.434</i>			<i>High</i>

Source: results of the Smart PLS

The analysis results presented in Table 3 indicate a high level of relative importance for **quality of customer service** within small and medium-sized enterprises (SMEs); the overall mean

score for business intelligence was 4.434, with the means of its individual dimensions ranging from 4.542 to 4.321. The "assurance/security" dimension ranked first (mean: 4.542; standard deviation: 0.898), while the "Reliability" dimension ranked last (mean: 4.321; standard deviation: 0.854). These findings highlight the significant relative importance of all **quality of customer service** dimensions and demonstrate the commitment of SMEs to adopting these dimensions within their operations to address evolving customer trends and changing needs

Measurement Model Assessment

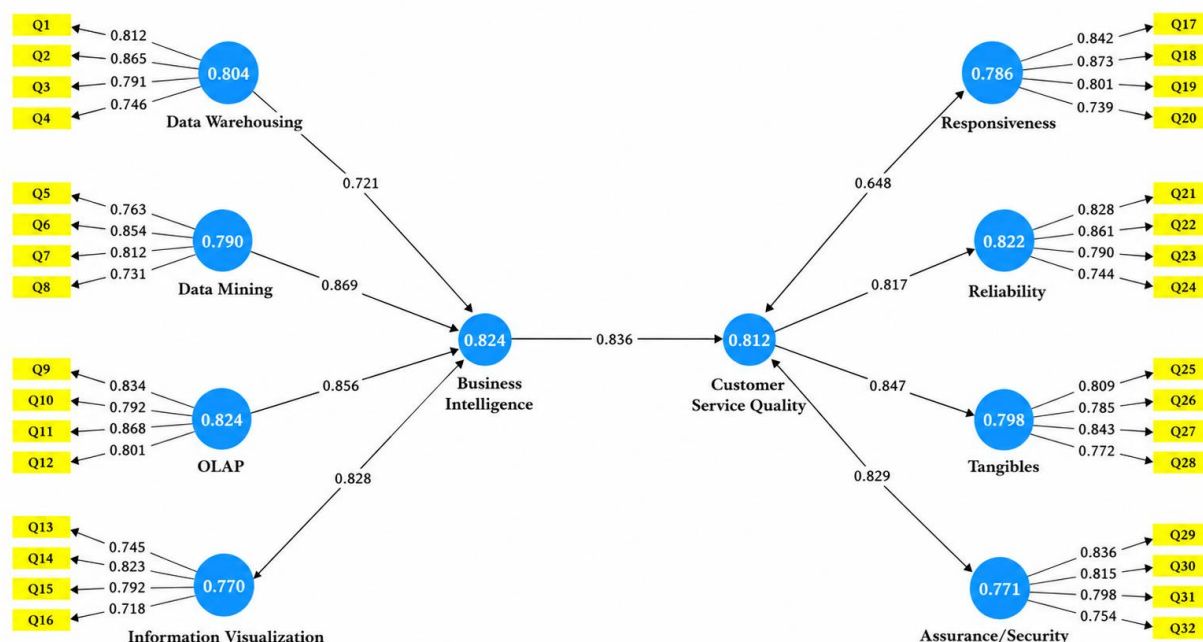
In this article, we employed the reflective measurement model, which is grounded in classical test theory. It is termed a "reflective model" because it relies on the fundamental premise that the measured indicators reflect the underlying latent variables influencing them; in this model, the direction of influence flows from the latent variable to the indicators—the reverse of what occurs in formative models (Hair et al., 2022, 51–52).

Convergent Validity

This analysis demonstrates the degree of convergence among the items of the study instrument (the questionnaire) used to examine the variables and their dimensions, and it also indicates the strength of the correlation between these items in measuring the variable and its dimensions (Hair et al., 2019). Table (5) presents the convergent validity indicator, which was assessed using factor loadings, composite reliability, and Cronbach's alpha, as well as the Average Variance Extracted (AVE).

Factor Loading

Figure 1 illustrates the factor loading values. Hair et al. (2022: 23) emphasize the importance of the values for study instrument items being greater than or equal to 0.7. Table 4 shows that all these values exceeded the required minimum threshold—surpassing 0.7—as is also illustrated in Figure 1.



Source: Prepared by the researcher based on the results of the Smart PLS.

Source: Results of the Smart PLS.

Table 4

Convergent Validity Indicator

variable	Dimensions	Items	Loading 0.70≤	Cronbach's Alpha 0.70≤	CR 0.70≤	Extracted contrast rate AVE 0.50≤
Business Intelligence	<i>data</i>	Q1	0.813	0.804	0.871	0.611
		Q2	0.865			
	<i>warehousing</i>	Q3	0.791			
		Q4	0.746			
	<i>data mining</i>	Q5	0.763	0.790	0.884	0.621
		Q6	0.854			
		Q7	0.812			
		Q8	0.731			
	<i>Online Analytical Processing (OLAP) information visualization</i>	Q9	0.834	0.824	0.865	0.598
		Q10	0.792			
		Q11	0.868			
		Q12	0.801			
Customer Service Quality	<i>responsiveness</i>	Q13	0.745	0.770	0.870	0.583
		Q14	0.823			
		Q15	0.792			
		Q16	0.718			
	<i>reliability</i>	Q17	0.842	0.786	0.871	0.610
		Q18	0.873			
		Q19	0.801			
		Q20	0.739			
	<i>tangibles</i>	Q21	0.828	0.822	0.845	0.636
		Q22	0.861			
		Q23	0.790			
		Q24	0.744			
	<i>assurance/ security</i>	Q25	0.809	0.798	0.873	0.598
		Q26	0.785			
		Q27	0.843			
		Q28	0.772			
		Q29	0.836	0.771	0.821	0.543
		Q30	0.815			
		Q31	0.798			
		Q32	0.754			

Source: Results of the Smart PLS

Heterotrait—Monotrait Ratio of Correlations (HTMT)

In the HTMT test, values below 0.9 serve as positive evidence of a causal structure among the study variables; consequently, it can be stated that the various variables are well-associated with the specific individual variable under study (Henseler et al., 2015, 115–135).

Table 5

Discriminants Validity using HTMT

Dimension	data warehous ing	data mining	(OLAP)	information visualization	responsiveness	reliability	tangibles	assurance/ security
data warehousing	0.718							
data mining	0.704	0.873						
(OLAP)	0.601	0.748	0.700					
information visualization	0.702	0.788	0.621	0.700				
responsiveness	0.703	0.753	0.686	0.689	0.817			
reliability	0.631	0.806	0.685	0.688	0.858	0.950		
tangibles	0.707	0.837	0.761	0.712	0.810	0.967	0.824	
assurance/ security	0.625	0.803	0.555	0.565	0.658	0.655	0.534	0.582

Source: Results of the Smart PLS

R² & R² Adjusted

The R² coefficient represents the proportion of explained variance, with values ranging from 0 to 1; a value close to 1 indicates higher predictive power and explanatory capability within the sample.

Table 6

Coefficient of Determination R²

	R ²	R ² Adjusted	Results
Customer Quality	0.731	0.722	High

Source: The results of the analysis

Table 6 presents the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2). The adjusted R^2 is considered a superior metric to the traditional measure, as it accounts for the number of explanatory variables relative to the dataset size (Hair et al., 2021, p. 119). According to guidelines for analyzing two-level hierarchical item models, the values of sub-dimensions (lower-Rank variables) should not be considered; instead, attention should be focused solely on the values of higher-order variables (Sarstedt et al., 2020). The analysis results revealed a close alignment between the R^2 and Adjusted R^2 values, indicating the model's goodness-of-fit and demonstrating the absence of variables that fail to contribute significantly to explaining the dependent variable. Specifically, the results showed an R^2 value of 0.710 for customer service quality—a high value—indicating that negligence intelligence explained 73.1% of the variance in customer service quality.

Predictive Model Strength Assessment

Table 7

PLS Path Model for Latent Variables (LV)

Variable	Q ²	RMSE	MAE
Customer Services Quality	0.670	0.568	0.442

Source: The results of the analysis

Table 7 shows that all predict Q^2 values for the indicators of the internal business intelligence variables in the study model are greater than zero. This demonstrates the superiority of the Partial Least Squares (PLS) path model over the simple benchmark in terms of predictive power, as the prediction errors in the PLS path model are mostly lower than those of the simple benchmark (Hair et al., 2022, 201).

Hypothesis Testing

H01: *Business intelligence with its dimensions of data warehousing, data mining, Online Analytical Processing (OLAP), and information visualization—does not improve the quality of customer service across its dimensions of responsiveness, reliability, tangibles, and assurance/security.*

Table 8

Path Coefficients of the Main Hypothesis

	(β)	R^2	t statistics	p values	Confidence Intervals (%95)	Moral Significance (p < 0.05)
BI - > Customer Services Quality	0.643	0.731	7.312	0.000	[0.811-0.410]	Supported

Source: Results of the analysis

Data from (Table 8) highlights a statistically significant relationship between business intelligence and customer services quality, supported by a beta coefficient of 0.643 and a significance level of $p = 0.000$ (which falls well below the standard 0.05 threshold). Furthermore, the calculated t-value of 7.312 comfortably surpasses the critical threshold of

1.96, while the confidence interval ranging from [0.811 to 0.410] underscores the stability of these path coefficient estimates.

These findings point to a strong, positive link, revealing that business intelligence drives a 73.12% impact on customer services quality. Assuming all other factors remain constant (*Ceteris Paribus*), a single-unit boost in business intelligence translates to a 73.21% improvement in overall quality for small and medium-sized enterprises.

Additionally, the coefficient of determination R^2 registered at 0.731, meaning that the model's variables account for 73% of the variance in customer services quality, leaving the remaining 27% to external factors not captured in this framework. This robust explanatory power speaks volumes about the model's overall quality and reliability.

Consequently, the null hypothesis is rejected in favor of the alternative. This confirms that the dimensions of Business intelligence with its dimensions of data warehousing, data mining, Online Analytical Processing (OLAP), and information visualization—exert a statistically significant influence on the dimensions of the quality of customer service across its dimensions of responsiveness, reliability, tangibles, and assurance/security in Small and medium-sized enterprises in Jordan.

Conclusion

In the dynamic, change and highly competitive business environment, (SMEs) face a continuous pressures to enhance their service quality and customer satisfaction. The primary objective of this research is investigate the impact of Business Intelligence through its various dimensions on enhancing customer service quality in SMEs. Utilizing structural equation modeling via SmartPLS, the article analyzed empirical data collected from the target sample. The empirical findings reveal a direct, positive, and statistically significant effect of business intelligence dimensions on customer service quality. Notably, the model demonstrated a robust explanatory power, with an R-squared R^2 value of 0.731 indicating that 73% of the variance in customer service quality is successfully explained by the business intelligence dimensions included in this study. Furthermore, all hypothesized paths were supported, confirming that every dimension of Business intelligence plays a vital role in shaping superior service outcomes.

Recommendations , Practical & Managerial Implications:

Contextually, this research fulfills a crucial role in supporting the operational development and sustainable growth of Small and medium-sized enterprises. By better understanding how **BI** drives service excellence, decision-makers and managers in this sector can:

Refine Strategic Planning: Leverage Business intelligence insights to make more effective, data-driven decisions that align with customer expectations. **Optimize Resource Allocation:** Direct investments toward core intelligence capabilities that yield the highest impact on customer retention and satisfaction.

Enhance Service Delivery: Transition from reactive approaches to proactive, intelligent customer service management.

Overall, this article contributes significantly to enriching the existing literature on BI and service management in SMEs, while providing a solid, evidence-based foundation for future academic research and organizational development in this vital sector.

References

- Abid-allah, S. (2009). Total quality management: A theoretical approach and process toward instilling a culture of quality and applying excellence standards. Dar Zahran for Publishing and Distribution.
- Abu Al-Nasr, M. M. (2015). Total quality management: Japanese Kaizen strategy for organizational development. The Arab Group for Training and Publishing.
- Ahmadi, H., Valipour, H., & Jamali, G. (2021). Relationship between business intelligence components and financial reporting quality in firms. *Journal of Optimization in Industrial Engineering*, 14(2), 155-167.
- Akter, S., et al. (2021). The impact of business intelligence information quality on front-line employee empowerment in the telecommunications sector. *International Journal of Information Management*, 58, 102-115.
- Al-Hakami, W. A., Al-Habib, R. A., Montash, M. A., & Badran, N. A. (2022). The impact of applying total quality management practices on improving health services quality: An applied study on Al-Noor Specialist Hospital in Makkah Al-Mukarramah. *Global Academic Journal of Economics and Business*, 4(1), 80-100.
- Al-Nsour, M., et al. (2024). The role of business intelligence technology in elevating the quality of customer services in the banking sector. *Journal of Business Research and Information Systems*, 12(1), 45-60.
- Alomari, A. Y., & Çengel, Ö. (2023). The effect of business intelligence on the development of human resources in Jordanian banks. *International Journal of Multidisciplinary Research and Growth Evaluation*, 4(4), 864-871. <https://doi.org/10.54660/IJMRGE.2023.4.4.864-871>
- Alshehadeh, A., Elrefae, G., Belarbi, A., Qasim, A., & Al-Khawaja, H. (2023). The impact of business intelligence tools on sustaining financial report quality in Jordanian commercial banks. *Uncertain Supply Chain Management*, 11(4), 1667-1676. <http://dx.doi.org/10.5267/j.uscm.2023.7.002>
- Al-Tuwaisl, A. A., & Al-Abbadi, S. S. (2018). Green supply chain management GSC. Dar Al-Yazouri for Publishing.
- Awad, H. A., & Mahmoud, Y. (2024). Impact of business intelligence (BI) on e-hrm practices within Ngos in Jordan. *Calitatea*, 25(200), 10-20. <https://doi.org/10.47750/QAS/25.200.02>
- Bajgoric, N. (2010). Always-On enterprise information systems for business continuance. Business Science Reference.
- Besterfield, D. H., Besterfield-Michna, C., Besterfield, G. H., & Besterfield-Sacre, M. (2018). Total Quality Management (5th ed.). Pearson.
- Binzafrah, F., & Taleedi, F. (2022). The effect of business intelligence practices on job satisfaction in the Saudi electricity company in the asir region. *Journal of Money and Business*, 2(1), 107-131. <https://doi.org/10.1108/JMB-03-2022-0011>
- Bussa, S. (2023). Enhancing BI tools for improved data visualization and insights. *International Journal of Computer Science and Mobile Computing*, 12(2), 70-92.
- Chaudhuri, S., Dayal, U., & Narasayya, V. (2023). An Overview of Business Intelligence Technology. *Communications of the ACM*, 54(8), 88-98.

- Gupta, K., Soni, K., & Saxena, K. (2021). Impact of strategic intelligence on organizational excellence: An empirical study on business units. *Turkish Online Journal of Qualitative Inquiry*, 12(3), 513-528.
- Hair, J. F., & Sarstedt, M. (2021). Explanation Plus Prediction—The Logical Focus of Project Management Research. *Project Management Journal*, 52(4), 319-322. <https://doi.org/10.1177/8756972821999945>
- Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling [PLSSEM] (2 nd ed.). Sage.
- Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling [PLSSEM] (3rd ed.). Sage.
- Hair, J. F., Jr., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). Advanced issues in partial least squares structural equation modeling. Sage.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2-24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Ibrahim, F. A. Z. (2022). Improving the quality of administrative services for distinguished program students in the Faculty of Education at Benha University using the SERVPERF actual performance model. *Journal of the Faculty of Education*, 19(113), 78-152. <https://dx.doi.org/10.21608/jfe.2022.242775>
- Johnson, M., & Smith, R. (2024). The Role of Business Intelligence in Achieving Competitive Advantage for Modern Organizations. *Journal of Management Information Systems*, 15(2), 45-68.
- Junaedi, A. T., Renaldo, N., Yovita, I., & Veronica, K. (2023). Development of digital economy teaching materials: Basic concepts of business intelligence. *Reflection: Education and Pedagogical Insights*, 1(2), 51-61. <https://doi.org/10.61230/reflection.v1i2.28>
- Kale, V. (2015). Inverting the paradox of excellence: How companies use variations for business excellence and how enterprise variations are enabled by SAP. CRC Press.
- Kazemi, A., Kazemi, Z., Heshmat, H., Nazarian-Jashnabadi, J., & Tomášková, H. (2023). Ranking factors affecting sustainable competitive advantage from the business intelligence perspective: Using content analysis and f-topsis. *Journal of Soft Computing and Decision Analytics*, 2(1), 39-53. <https://doi.org/10.31181/jscda21202330>
- Lamani, A., Erraha, B., Elkyal, M., & Sair, A. (2019). Data mining techniques application for prediction in OLAP cube. *International Journal of Electrical & Computer Engineering* (2088-8708), 9(3), 2094-2102.
- Lawson, J. (2021). *Business Analytics: Transforming Big Data into Intelligent Decisions*. Wiley Publications.
- Lin, Y., et al. (2023). Integrating business intelligence and big data analytics for customer relationship management strategies in e-commerce. *Computers in Human Behavior*, 140, 107-122.
- Manikam, S. & Sahibudin, S. & Kasinathan, V. (2019). Business intelligence addressing service quality for big data analytics in the public sector. *Indonesian Journal of Electrical Engineering and Computer Science*, 16(1), 491-499. <http://dx.doi.org/10.11591/ijeecs.v16.i1.pp491-499>
- Mbima, D., & Tetteh, F. K. (2023). Effect of business intelligence on operational performance: The mediating role of supply chain ambidexterity. *Modern Supply Chain Research and Applications*, 5(1), 28-49. <https://doi.org/10.1108/MS CRA-08-2022-0020>

- Natarajan, A. K., & Galety, M. G. (2024). Intersection of AI and business intelligence in data-driven decision-making. IGI Global.
- Obeidat, B., et al. (2023). Assessing the effect of business intelligence capabilities on marketing performance and service quality in SMEs. *VINE Journal of Information and Knowledge Management Systems*, 53(2), 240-258.
- Parasuraman, A., Zeithaml, V., & Berry, L. (1985). A conceptual model of services quality and its implications. *Sage Journal*, 49(4), 41-50. <https://dx.doi.org/10.1177/002224298504900403>
- Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7(3), 213–233. <https://doi.org/10.1177/1094670504271156>
- Qattaf, F., & Bazqarari, A. (2019). *Banking Service Quality*. Osama Publishing and Distribution House.
- Reiss, K., et al. (2022). *Fundamentals of Data Analysis and Business Intelligence*. Academic Press.
- Richards, G., Yeoh, W., Chong, A. Y. L., & Popovič, A. (2019). Business intelligence effectiveness and corporate performance management: an empirical analysis. *Journal of Computer Information Systems*, 59(2), 188-196. <https://dx.doi.org/10.1080/08874417.2017.1334244>
- Rosita, A. & Wulandari, M. (2021). Introduction study of business intelligence hospital medical recording data. *Turkish Journal of Computer and Mathematics Education*, 12(11), 1043-1050.
- Sabherwal, R., & Fernandez, I. B. (2011). *Business intelligence: Practices, technologies, and management*. John Wiley & Sons.
- Sechi, G. M., Migliori, m., Dassi, G., Pagliosa, A., Bonora, R., Alacreu, A. O., Odone, A., Signorelli, C., & Zoli, A. (2020). Business intelligence applied to emergency medical services in the lombardy region during SARS-CoV-2 epidemic. *Official Journal of the Society of Medicine and Natural Science of Parma*, 91(2), 39-44. <https://dx.doi.org/10.23750/abm.v91i2.9557>
- Sekaran, U. & Bougie, R. (2016). *Research Methods for Business: A Skill-Building Approach*. (7), Wiley & Sons, West Sussex.
- Sherman, R. (2015). *Business intelligence guidebook: From data integration to analytics*. Newnes.
- Tahar, N., & Maiouf, K. (2019). The contribution of electronic management in improving the quality of public services: A case study of the General Directorate of Taxes. *Namaa Journal for Economy and Trade*, 3(2), 17-35. <https://search.emarefa.net/detail/BIM-1089362>
- Van Iwaarden, J., van der Wiele, T., Ball, L., & Millen, R. (2003). Applying SERVQUAL to Web sites: An exploratory study. *International Journal of Quality & Reliability Management*, 20(8), 919-935. <https://doi.org/10.1108/02656710310493634>
- Watson, H. J. (2023). Tutorial: Business Intelligence—Past, Present, and Future. *Communications of the Association for Information Systems*, 25(1), 39-50.
- Yassin, S. G. (2018). *Management information systems MIS*. Dar Al-Yazouri Scientific for Publishing and Distribution.